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Simulating plant water stress dynamics in a wide range of bi-specific agrosystems in a region using the BISWAT model

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A B S T R A C T

The ability to simulate soil and crop processes in many bi-specific systems (vineyards, orchards, silvo-arable agroforestry, strip-intercropping of arable crops…) is one of the major challenge for crop modelling in order to contribute to the design of agro-ecological cropping systems. A typical question is how soil, climate and management would influence the soil water deficit experienced by a plant grown alone or intercropped with a cover crop, with another crop or a tree, in order to improve the resilience of a cropping system to climate change and limit the use of chemical input.

This study introduces BISWAT – Bispecific Intercrop System WATer Stress dynamic model - a new water balance model designed to simulate the dynamic of Soil Water deficit Experienced (SWEP) by two Plants when grown together or separated. BISWAT has been built to simulate a large range of agrosystems (annual and perennial crops, mono- or bi-specific) cultivated in various conditions. The model is primarily based on three modelling concepts: i) a 2D generic pattern for the system's spatial representation, ii) the use of the Radiation Interception Efficiency (RIE) to drive potential plant transpiration and soil evaporation, iii) the use of the Total Transpirable Soil Water (TTSW) concept coupled with a simple root dynamics representation. These concepts are not new but they allowed us to define a model able to simulate many crops and trees (including vineyards) using a limited number of inputs and without an explicit need for parameter calibration.

The model was evaluated on five reference agrosystems (mono-specific salads, mono-specific vineyards, bi-specific vineyards, mono-specific peach orchards and bi-specific peach orchards). The RMSE of the SWEP variable ranged from 0.049 to 0.123. A combined sensitivity and uncertainty analysis performed on typical farmer's fields situations stressed the particular importance of model inputs related to the TTSW of the soil-crop system.

We conclude that the genericity of the BISWAT model, its method of parameterization and its performance open the perspective to use the model in a wide range of conditions where the dynamic of water stress between two species grown together is a key variable to be accessed with limited data for parameterization and a large number of fields to simulate.

1. Introduction

Throughout the process of input based intensification - aimed to increase land productivity- and of mechanization -aimed to increase labor productivity- cropping systems have been simplified over the past 50 years in most regions of the globe. Beyond farm specialization (for example on arable crop or on horticultural crops) and/or the reduction in the number of crops in a rotation, the major shift in the agronomic paradigm was to consider that a field is occupied by only one plant species and most often one variety (e.g. in wheat) or one clone (e.g. in vineyards) (Gaba et al., 2015). This has largely shaped the development of crop modelling which currently offers a large number of models for a single crop when grown as a single species, single variety and without weeds (eg. 27 models for wheat simulation in Asseng et al., 2013). The same trends occurred with trees and vineyards with some models for a monospecific orchard (e.g. Rana et al., 2005 on citrus trees) or a homogeneous forest plantation (Granier et al., 1999). But very few models are currently available to simulate, for example, an annual plant intercropped into trees alleys (Malézieux et al., 2009) or strip-intercropping of maize and wheat (Gaba et al., (2015). As recognized by Luedeling et al. (2016) the simulation of interactions between trees and arable crops inside an agroforestry system under water and nutrient limited conditions is still a challenge for modelers. This is in contrast with the growing needs of simulation of plurispecific systems

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(Malézieux et al., 2009) to support the design and management of cropping systems less dependent on pesticides and fertilizers and that can provision ecosystems services beyond crop production (Gaba et al., 2015). A typical example can be found in vineyards where these environmental concerns are driving the re-complexification of these agrosystems (as defined by Lamanda et al., 2012) with intercropping of grasses, cover crops and green manure, in order to replace herbicides use and bare soil prone to erosion or to limit plant vigour and therefore susceptibility to pests and diseases (Ripoche et al., 2010). Another example is provided by the growing interest in Europe (Eichhorn et al., 2006) and elsewhere (Luedeling et al., 2016) for the silvo-arable agroforestry systems where the intercropping of timber or fruit trees and cereals or vegetables is expected to provide resilience to climate change and improve soil quality and ecosystems services. On the other hand, traditional intercropped systems, for example with olive trees, in small holder farms in north Africa (Makhzoumi, 1997), are challenged as to their resilience to climate change and for their contribution to national food security.

The ability to simulate soil and crop processes in these bi-specific systems (vineyards, orchards, silvo-arable agroforestry, strip intercropping of arable crop …) is one of the major challenges for crop modelling, if it has to contribute to the design of agro-ecological cropping systems (Gaba et al., 2015) as currently done for monospecific crop rotations (Bergez et al., 2010). Models are likely to be increasingly used to explore a wide range of combination patterns of species and management (e.g. number of trees per row, distance between tree rows, width and phenology of the intercropped strip, irrigation, etc.) to address climate and soil variability (Talbot et al., 2014). In order to analyze the benefit of intercropping, for example on Land Equivalent Ratio or on resilience to climate change, they should also allow for the simulation of each of the species as a monospecific crop, orchard or forest (Talbot et al., 2014) or in comparison with bare soil for orchards or vineyards (Ripoche et al., 2010). Among the burning questions to address in this comparison of bi-specific versus mono-specific agrosystems is their influence on the water balance (Luedeling et al., 2006), in order to analyze the soil water deficit experienced by each plant-species and to quantify some water flows (runoff, percolation) which are the driving functions of ecosystems services and of their trade-offs. Forexample Ripoche et al. (2010) show how such type of model can be used for the simulation of water flows and water stress experienced by vine, when in competition with a grass cover intercrop, in order to explore the tradeoffs between 4 ecosystems services: sensitivity to pests and disease (through reduced vine vegetative growth by the water stress induced by cover crop), yield, grape quality, reduced runoff. We therefore identify a need for models able to simulate the water balance of a wide range of crops/trees species (including vineyards and orchards) either grown alone or in a "bispecific agrosystem" (e.g. a row crop composed of two plants species and a soil) and for a wide range of spatial and temporal combinations of these two species in a field.

A first way to develop such type of model is to extend or link existing crop models and tree models in order to benefit from previous and on-going developments of each of these "monospecific models" (e.g. CERES for arable crops (Hammad et al., 2017)) in term of processes taken into account and of parameters available for each species (Luedeling et al., 2016). This is typically what has been done for agroforestry and intercropped orchards and vineyards, with the Hi-Safe (Talbot et al., 2014), APES (Donatelli et al., 2010) and APSIM (Huth et al., 2003) models. Beyond the genericity for plants species and association patterns these so-called "integrated models" aim to also integrate a wide range of soil and crop processes (especially plant competition for nutrients, in interaction with water and their effect on yields of both plant species) (Luedeling et al., 2016). These models are therefore data intensive for parameterization, even if used only for their water balance component, with an uncertainty difficult to control (Passioura, 1996) and at some point difficult to use outside of research projects (Luedeling et al., 2016).

The alternative is to develop what we define here as a "partial model" representing a limited part of the agrosystem's components and processes (Lamanda et al., 2012), and therefore addressing specific questions in a validity domain restricted to a particular sub-set of soil-plant processes, in our case the water balance. This *ad hoc* approach of modelling (Affholder et al., 2012) is based on the assumption that 'the right model' is the one which is built in the three-way nexus between "process at stake/data available for parameterization/affordable uncertainty in a situation of model use" (Adam et al., 2013).

As presented above, a typical type of problem requiring the use of a partial simulation model for bi-specific agrosystems is how soil, climate and management influence the soil water deficit experienced by a plant (Pellegrino et al., 2006) when grown alone or intercropped with a cover crop, another crop or a tree in a wide range of conditions across a region. This information may be needed to design intercropped systems more resilient to climate change (Ripoche et al., 2010), to diagnose the occurrence of water stress in a network of farmers' fields (Pellegrino et al., 2006) or to schedule irrigation of one or of the two crops in association (Roux et al., 2014b). Another example of new model requirements is decision support tools (DST) needed by industrials and territorial collectivities to improve resources management (Arnold et al., 2012) and anticipate the water demand explosion at a region scale during drought periods, where many farmers may need water for irrigation at the same time. In most of the above cases the model should be able to represent all types of agrosystems managed by farmers in the region: arable crops, vegetables, orchards, vineyards either grown alone or in association (Bertrand and Wery, 2017). For all of these examples, the question of data availability for parameterization at a reasonable cost, in order to make possible the use of a simulation model outside of research, is crucial. It implies two desired properties for models: the first one is the possibility to use a model without having to measure some variables specifically to perform a parameter calibration (i.e. adjusting some of the parameters on model output variables measured in the target situations). The second one is to have a clear link between all model inputs (variables and parameters) and biophysical processes so that expert knowledge may be used to assist model parameterization when data are lacking, which is the most frequent situation when model are used outside of research stations (Roux et al., 2014a,b).

Several 'partial' crop models centered on water flows modelling have been developed for monospecific cropping systems (mostly arable crops), such as the SWAT model (Arnold et al., 2012) widely used for hydrological simulations at regional levels and the CropWat model (Paredes et al., 2014) widely used for the simulation of water limited yields depending on climate, soil and crop management. There are few attempts of partial models dedicated to the simulation of water balance of bi-specific systems, and they only propose models dedicated to a specific type of association such as wheat-maize or wheat-sunflower strip intercropping (Miao et al., 2016), olive orchards intercropped with potato or pea (Abid Karray et al., 2008) or barley and weeds (Abazi et al., 2013), vineyards inter-cropped with barley or with tall fescue (Celette et al., 2010) or grass mixtures (Montes et al., 2014).

Apart from Montes et al. (2014), all these models have in common to rely on the FAO approach based on the Kc concept (Allen et al., 1998) or to an extension of this approach (Paredes et al., 2014), for crop evapotranspiration calculation. In these models plant interactions are limited to water competition and modification of the transpiration demand to the shaded crop. Water competition is mostly computed in these models by defining independent water uptakes in shared water reservoirs. The effect of the dominant crop on the shaded crop transpiration demand is either defined by developing a multi-source evaporation model (Montes et al., 2014), by computing a dedicated crop coefficient of the inter-crop using the dominant crop height (Miao et al.,2016), by using the light interception efficiency of the dominant crop to reduce ET0 (Celette et al., 2010) or is neglected (Abid Karray et al., 2008 and Abazi et al., 2013).

These models have been designed and tested mostly for agrosystems

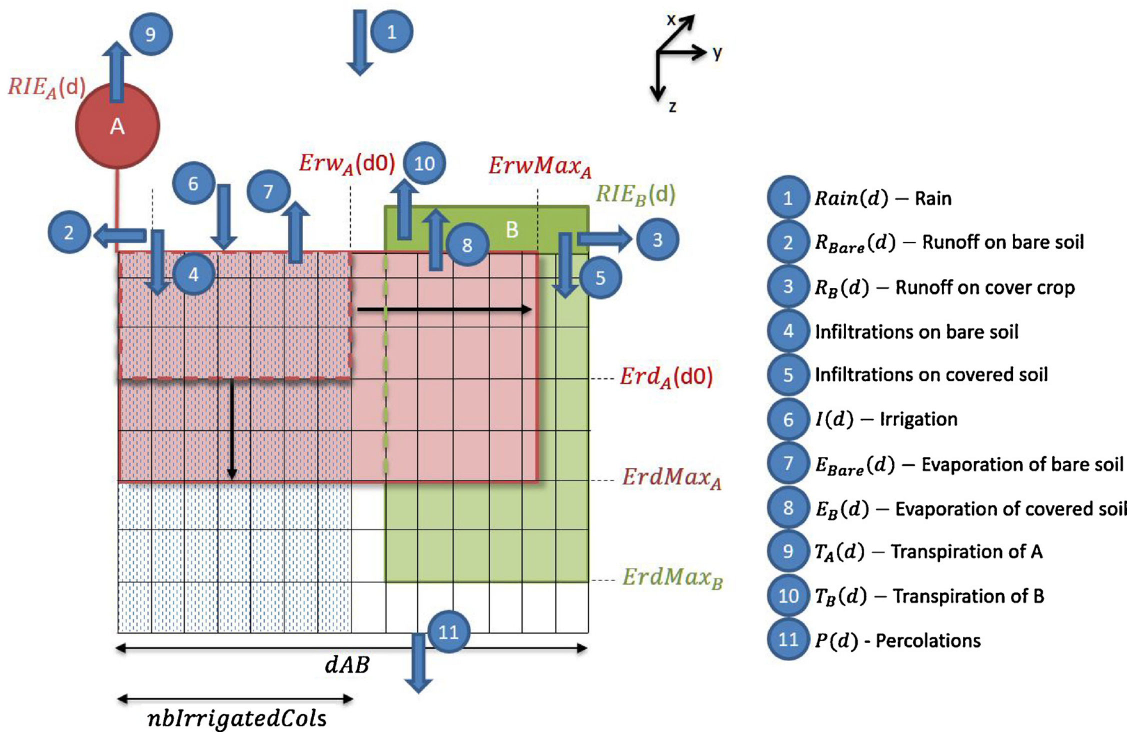

Fig. 1. The generic agrosystem conceptualization in BISWAT using a 2D pattern and a flexible spatial representation of the system. The 11 main water flows are represented along with the main variables describing the geometry of the system.

based on one specific crop and they lack the possibility to be easily extended to handle almost any mono and bi-specific systems. Among these models, the models for inter-cropped vineyards (Celette et al., 2010) and for inter-cropped orchards (Abid Karray et al., 2008) are the most interesting in terms of extensibility. The formulation of the inter-cropped vineyards model, which extends previous works on mono-specific vineyard water stress modelling (Lebon et al., 2003; Riou et al., 1989) is closer to our modelling objectives since it does not require parameters calibration on measured soil water content for the plant transpiration process.

The objective of this work is to introduce the new simulation model named BISWAT (Bispecific Intercrop System WATer stress dynamics model), focused on plant water stress modelling taking into account modelling constraints identified above, namely the need to limit model complexity in order to reduce the difficulty of parametrization and make it usable in a wide range of crops (including vegetables) and trees (including orchard and vineyards) and their dual combinations. The novelty we claim is not in the modeling concepts per se but in the way they have been combined and adapted to ease parameter estimation with simple measurements and local expertise for a wide range of bi-specific systems outside of research stations. BISWAT can be seen as an extension of the model for inter-cropped vineyards (Celette et al., 2010) with many extended formalisms allowing to simulate the water stress dynamics, at a daily time step and at field scale, for a wide range of crops cultivated in rows (especially annual crops like vegetable crops or field crops and perennial crops like vineyards or orchards) and for a large range of mono or bi-specific agrosystems. It allows to simulate various irrigation practices like localized or full coverage irrigation; various soils with different soil occupation as bare soil, plastic covering or intercropping; and various range of water stress levels and dynamics depending on crop types and yield objectives.

In this paper we will first describe in Section 2 the main modelling concepts, the main mathematical formalisms and the resulting list of model inputs of the BISWAT model. We then present the parameterization (Section 3.1) and the evaluation (Section 3.2) of the model performed on 5 reference agrosystems: mono specific salads cultivated under plastic shelters, mono and bi-specific mature vineyards, mono specific and bi-specific young peach orchards. We finally present in Section 3.3 the results of several sensitivity analyses conducted to identify the most sensitive inputs of the model in typical situations of model use outside of research stations were data availability if often limited (Roux et al., 2014b). Section 4 discuss the model validity domain and parameterization protocol and Section 5 concludes on the model originality and potential for further uses.

2. Materials and methods

2.1. Model description

In this part, a description of the BISWAT model is presented by focusing on modelling choices and concepts, and by describing mathematical formalisms which are at the model core.

The model simulates the water stress dynamics of 2 plants generically denoted as *A* (generally the main plant in economical terms) and *B* (the intercrop). Both A and B can be an annual or a perennial plant such as tree or a vine. For each plant component of the agrosystem (A and B), water stress is modeled by the Soil Water deficit Experienced by a Plant (SWEP) state variable at a daily timestep. It is based on the Fraction of Transpirable Soil Water (FTSW) concept (Sinclair and Ludlow, 1986) which has been shown to be closely related to the predawn leaf water potential and to plant transpiration and growth processes, both in annual plants (e.g. coton, Lacape et al., 1998) and in perennial plants (e.g. grapevine, Pellegrino et al., 2004). The use of this generic concept allows to take into account both soil and plant characteristics for the quantification of water stress experienced by A and B plants (SWEP) and its impact on plant processes (Pellegrino et al., 2006). For day *d* and a plant *X* (*X* being A or B), the expression linking SWEP and FTSW is the following:

$$SWEP_X(d) = 1 - FTSW_X(d) \quad (1)$$

2.1.1. Possible crops combinations and spatial representation of the system

In order to model a tree and/or a crop and to manage sowing, destruction and rotations, the modeled agrosystem has potentially nine states which correspond to different combinations of {Tree, Crop, Nothing i.e. bare soil)} for both A and B. All combinations are currently managed by the model except the association of two trees (it would have required to manage trees competition for radiation interception, depending on trees height and their growth) while in BISWAT species A is the tallest plant.

Both plants are interacting in a two-dimensional spatial pattern as represented in Fig. 1. This choice is made possible because we suppose that the system is homogeneous along the row direction and that the system is symmetrical on either side of the row. Therefore, the state variables of any agrosystem component (e.g. a soil layer) are supposed to have the same value independently of the position considered along the row direction. The width of the 2D spatial pattern, called dAB, corresponds to the half distance between two rows of A. Soil is sampled into rows and columns depending on user's choices from the knowledge he has of soil structure. The main state variable of a soil cell on day d is its humidity $\Theta^{ij}(d)$ (where i is the index for soil layers and j the index for soil columns), considered as homogeneous inside a cell. This sampling has been chosen such as: i) evaporation only occurs into the first soil layer (which by default has a thickness of 10 cm), ii) plant-specific (A or B) water extraction due to actual transpiration are possible and computed in coherence with root growth characteristics of each species iii) localized irrigation (e.g. drip irrigation) as well as a full coverage irrigation (e. g. spray irrigation) are possible.

2.1.2. The use of the TTSW concept coupled with simple roots dynamic representation

The use of the TTSW concept (Sinclair and Ludlow, 1986) in the context of the flexible soil sampling presented above requires the use of three soil/plant characteristics discretized in the z direction (an example is given in column 4 in Fig. 2). The first one is the lower limit of soil water content $\Theta^{-}(z)$ defined for each soil layer and under which the plant cannot extract soil water (this limit depends on soil characteristics such as soil texture, bulk density and stoniness, but also on plant characteristics such as roots density and iso/anisohydric plant behaviour). It has therefore a higher value of soil water content than the permanent wilting point as shown, for example, by Pellegrino et al. (2004) for vineyards. It can either be measured with soil water content in the field (with the protocol described by Pellegrino et al., 2004) or by default estimated from soil wilting point and plant characteristics as described in the BISWAT parameterization protocol (available upon request to the authors). The second one is the upper limit of soil water content $\Theta^{fc}(z)$, the field capacity per soil layer, which depends on soil characteristics only. The third one is the dynamic root system boundary in both directions (z and y) described with the Effective Rooting Depth ($Erd(d)$) concept, as defined by Lacape et al., (1998) and that we propose to extend to lateral root growth, with the Effective Rooting Width ($Erw(d)$) (see Fig. 1). Roots growths are simply driven by the accumulated degree days in both directions for trees and only in depth for crop (in this case, $Erw(d)$ is a constant, defined by the width of the crop canopy). Using these three limits, the TTSW of each of the x plants (A and B) is calculated as a state variable by BISWAT (Eq. (2)). The implication of this approach is that A and B plants grown together in the same soil may have different TTSW and therefore may experience different soil water deficit (SWEP) for a given soil water content in its rooting zone.

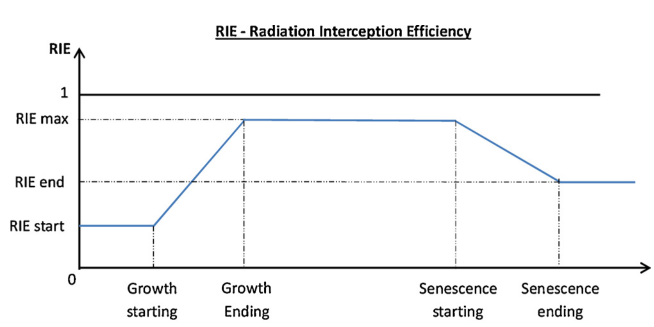

Fig. 2. Parameterization of the RIE of each crop of the agrosystem with expert knowledge when direct measurements are not available. Each parameter has a biophysical meaning and can apply to any crop or tree either grown alone or in combination.

$$TTSW_X(d) = \int_0^{Erd_X(d)} (\Theta^{fc}(z) - \Theta_X^{-}(z))\, dz \tag{2}$$

2.1.3. Computing transpiration and evaporation flows using a simple radiative balance and Radiation Interception Efficiencies (RIE)

We use in the BISWAT model radiation-driven expressions for computing transpiration and evaporation flows separately. This approach consists in using a simple radiative balance using the Radiation Interception Efficiency (RIE) of both species to compute the radiation intercepted by each agrosystem's component. This approach uses RIE as a surrogate of the Kc coefficient used for mono-specific crops in the FAO approach (Allen et al., 1998) and it generalizes the approach used for an intercropped vineyard by Celette et al., (2010). Trees (A component) are supposed dominant over crops (B component) for light competition, so only the radiation not intercepted by the tree may be used by the crop canopy for transpiration, the remaining radiation reaching the soil and driving evaporation. Transpiration flows $T_A(d)$ and $T_B(d)$ are then directly driven by the intercepted radiation, the climatic demand ($ET0$) which is a variable available in most climatic networks, and the soil water deficit experienced by A and B, each plant of the association having its specific level of water stress (Eqs. (3) and (4)):

$$T_A(d) = RIE_A(d).\ min\left(1, \frac{FTSW_A(d-1)}{0.4}\right).\ ET0(d) \tag{3}$$

$$T_B(d) = (1 - RIE_A(d)).\ RIE_B(d).\ \frac{width_B(d)}{width_{AB}}.\ min\left(1, \frac{FTSW_B(d-1)}{0.4}\right).\ ET0(d) \tag{4}$$

In both equations the threshold of FTSW below which plant transpiration is reduced is set at 0.4, a value which has been observed in field conditions for annual (Lacape et al., 1998) and perennial plants (Pellegrino et al., 2006). If experimental evidence of major differences are available for this parameter, an in conditions where TTSW is properly measured (see Pellegrino et al., 2004), it can be further modified in the equations, but for the sake of simplicity in model parameterization, we have considered these differences among species as minor in comparison with the differences in TTSW among species and soils.

Soil evaporation flows are also driven by the climatic demand ($ET0$) and the remaining radiation after light interception by tree and crop. Evaporation is regulated by the humidity of the upper soil layer. Following (Allen et al., 1998), this process takes place in two stages formalized using a reducing factor Kr: a stage where energy is limiting (no limitation by water, $Kr = 1$) and a second stage where available water is limiting (K_r proportional to the soil water content of the evaporating soil layer and computed for each soil cell). The adaptation of the approach from (Allen et al., 1998) to compute evaporation for a bare soil (state variable E_{Bare}) and under a cover crop (state variable E_B) while taking into account the proportion of bare soil ($width_{Bare}(d)$) and cover crop ($width_B(d)$) yields the following equations, which correspond to a case where soil humidity is homogenous in the upper soil layer:

$$E_{Bare}(d) = (1 - RIE_A(d)).\ \frac{width_{Bare}(d)}{width_{AB}}.\ K_r(d).\ ET0(d) \tag{5}$$

Table 1
List of model inputs required to run a simulation with the BISWAT model. ● indicates an input required for a crop, ○ indicates an input required for a tree and X indicates an input required only if plant roots are growing during the simulation.

Type of input	Name of input	Description	Unit	Input file
Simulation	StartDate	Date of first simulated day	–	parameters.csv
	Duration	Simulation duration	d	parameters.csv
2D modelling pattern	DistanceAB_mm	Width of the 2D pattern	mm	parameters.csv
	SoilZ_mm(z)	Depths of each soil layers	mm	parameters.csv
	SoilNbColumns	Number of columns	–	parameters.csv
	Width●	Width of the 2D pattern covered by a plant.	mm	parameters.csv
Weather	Temperature(d)	Daily average temperature	°C	input_variables.csv
	Rain(d)	Daily rain	mm	input_variables.csv
	ET0(d)	Daily reference evapotranspiration	mm	input_variables.csv
Radiation interception	RIE(d)	Daily Radiation Interception Efficiency of a plant canopy	–	input_variables.csv
TTSW	BaseTemperature[X]	Base temperature of a plant	°C	parameters.csv
	ErdMax_mm	Maximum Effective Rooting Depth of a plant	mm	parameters.csv
	ErwMax_mm○	Maximum Effective Rooting Width of a plant	mm	parameters.csv
	TsToReachErdMax[X]	Temperature sum to reach the maximal depth for a plant	°C	parameters.csv
	TsToReachErwMax[X]○	Temperature sum to reach the maximal width for a plant	°C	parameters.csv
	ThetaMinus(z)	Critical humidity for each soil layer for a plant	m3/m3	parameters.csv
	ThetaFC(z)	Field capacity for each soil layer	m3/m3	parameters.csv
Evaporation	ThreshEvap1_mm	Threshold below which there is no evaporation	mm	parameters.csv
	ThreshEvap2_mm	Threshold above which evaporation is not limited by drought	mm	parameters.csv
Runoff	Runoff_Bare_CN2	Curve number required to compute runoff on the bare soil	–	parameters.csv
	Runoff_CN2●	Curve number required to compute runoff on the cover crop	–	parameters.csv
Initial state	T0Theta	Soil volumetric water content for first simulated day	m3/m3	parameters.csv
	T0Id	ID of a plant already installed for first simulated day	–	parameters.csv
	T0Erd	Effective Rooting Depth for the first simulated day	mm	parameters.csv
	T0Erw	Effective Rooting Width for first simulated day	mm	parameters.csv
Crop calendar	Sowing	Sowing date(s)	–	crop_calendar.csv
	Destruction	Destruction date(s)	–	crop_calendar.csv
	Irrigation	Quantity of irrigation (+ dates and impacted soil cells)	mm	crop_calendar.csv

$$E_B(d) = (1 - RIE_A(d)).\ (1 - RIE_B(d)).\ \frac{width_B(d)}{width_{AB}}.\ K_r(d).\ ET0(d) \tag{6}$$

Unlike most other models, we chose to define RIE as an input variable in the model. Therefore RIE can be seen as a surrogate of the crop coefficient (Kc) used in many models such as CropWat (Paredes et al., 2014). But using directly RIE aims to allow for a more functional approach in the parameterization process for all types of crops and management as shown in Fig. 2. This modelling option, as well as in the Kc approach, means that there is no explicit simulation of the effect of water stress on the canopy development processes which are driving the dynamic of RIE. This may limit the use of the model in case of early water stress affecting plant leaf area, unless this is properly taken into account in the parameters of the first part of the RIE curve in Fig. 2. But for our targeted use in a large range of mono and bispecific crops in a region this approach offers a lot of flexibility in the model use and allows to parameterize the model for any type of crops and or trees and almost any type of management (plant spacing, nutrients deficiency, foliar diseases…) which impact the RIE dynamic. RIE can be estimated from measurements with sensor based equipments, or with a model dedicated to light interception (especially for trees) or from local experts having a good expertise of the crop species and management in farmers fields and using the approach described in Fig. 2. It is likely that when the objective is to model the water balance of any crop cultivated by farmers in a region, including orchards, vineyards and agroforestry, RIE measurements, as well as Kc value in the FAO approach, will be lacking for some if not all, and the parameterization approach proposed in Fig. 2 can make use of the practical knowledge of local experts. Letting RIE dynamic outside of the model opens the possibility to take into account un-modeled cropping practices (e.g. grass cutting or trees pruning) or un-modeled biophysical process (e.g. effect of plant spacing and nutrient deficiency on leaf canopy development) which are likely to occur in reality in the various fields of a given crop at regional level. This will be illustrated in the Results Section 3.1 and further discussed in Section 5.

2.1.4. Water balance modelling at the soil cell level

The water balance is computed by using SW^{ij} (d), the Soil Water content state variable calculated for each soil cell (i is the index for soil layers and j the index for soil columns). SW^{ij} (d) is updated each day by computing $\Delta Stock^{ij}(d)$, the water stock variation of the day, then it is bounded by the Total Soil Water of the soil cell (TSW^{ij}) which is reached when the soil cell humidity is at field capacity (Eq. (7)).

$$SW^{ij}(d) = min(TSW^{ij}, SW^{ij}(d-1) + \Delta Stock^{ij}(d)) \tag{7}$$

$\Delta Stock^{ij}(d)$ is calculated following the layer depth: For the first layer (i = 0), its computation involves $R^j(d)$, the daily rain, $R0^j(d)$, the daily runoff, $I^j(d)$ the daily irrigation, $E^j(d)$, the daily soil evaporation, $T_A^{ij}(d)$ and $T_B^{ij}(d)$, the daily plant transpiration uptaken in the soil cell for each crop (where calculation depends on each root system proportion in the cell but also on cell humidity for the first soil layer (Eq. (8)). This applies also for the lateral growth of roots, soil water being extracted in a cell on the day the roots reach it, until they arrive at the ERWmax. For the other layers (i > 0), the water fluxes are $P^{(i-1)j}$, daily percolations coming from the upper layer and $T_A^{ij}(d)$ and $T_B^{ij}(d)$ (see Eq. (8)). Runoff is computed using the curve number method (Boughton, 1989) and is calculated differently on a bare soil component and on the crop component. Percolation typically occur when field capacity is exceeded and excess of water is automatically drained into the lower soil layer. Other water fluxes such as lateral transfers, capillary rises or effects of the water table are neglected in the model, which implies that situations where one of these un-modeled processes is dominant are outside BISWAT validity domain.

$$\Delta Stock^{ij}(d) = \begin{cases} R^j(d) - R0^j(d) + I^j(d) - E^j(d) & \text{for the 1st layer } (i = 0) \\ \quad -T_A^{0j}(d) - T_B^{0j}(d) & \\ P^{(i-1)j} - T_A^{ij}(d) - T_B^{ij}(d) & \text{for the other layer } (i > 0) \end{cases} \tag{8}$$

2.1.5. Model inputs and outputs

The modelling concepts described above allow to build a simulation

Table 2
List of data used for evaluation specifying measurements (not parametrization).

Main crop	Type of agrosystem	Intercrop	Year	Irrigation	Location	Reference
salad	monospecific	polyethylene film	2000	spray irrigation	Plain of "Vistrenque", southern France	Gay (2002)
			2001			
			1999			
vineyard	monospecific	bare soil	2000	no	Roujan, southern France	Pellegrino et al. (2004)
			2001	drip-irrigation	Aspère, southern France	
			2011	no	Villeneuve-lès-maguelone, southern France	Guilpart et al. (2013)
			2012		Roujan, southern France	
	bispecific	pea	2001			Pellegrino et al. (2004)
		fescue	2004		Villeneuve-lès-maguelone, southern France	Celette et al. (2008)
		fescue	2005			
		fescue	2006			
peach orchard	monospecific	polyethylene film	2015	drip-irrigation	Mauguio, southern France	Forey et al. (2016)
	bispecific	grass-legume mixture				

model with a limited number of soil, crop and climate inputs easily available in most agricultural regions, which was one of the constrains set for the model design, in order to ensure operational application outside of research stations. Some of the choices we have made, such as the use of ETo provided by weather stations network as an input variable may be re-assessed leading to integrate in the model the calculation of ETo with simple equations which do not require air humidity and temperature.

Table 1 lists the main inputs and shows that the user has less than 30 inputs to set before running a simulation, more than half of them being easily deducted from the definition of the agrosystem to be simulated.

The main output of BISWAT is the SWEP dynamics (Soil Water Deficit Experienced by the Plant) for each of the two plants in association, based on the FTSW concept as seen in Eq. (1). FTSW is calculated for each plant (A and B) as the ratio of their ATSW (Available Transpirable Soil Water) to their TTSW (Eq. (9). $ATSW_X(d)$ and $TTSW_X(d)$ are both computed by integrating the water content in each soil cell weighted by $w^{ij}(d)$, a coefficient representing the proportion of the cell volume colonized by the roots and computed from both states variables $Erd_X(d)$ and $Erw_X(d)$. For each soil cell, $ATSW_X^{ij}(d)$ is defined as the difference between $\Theta^{ij}(d)$, the humidity of the day and $\Theta_X^{-,i}$, the low limit of the TTSW and $TTSW_X^{ij}(d)$ is defined as the difference between $\Theta^{fc,i}$, the field capacity and $\Theta_X^{-,i}$.

$$SWEP_X(d) = 1 - \frac{ATSW_X(d)}{TTSW_X(d)} = 1 - \frac{\sum_{ij} ATSW_X^{ij}(d)}{\sum_{ij} TTSW_X^{ij}(d)} = 1 - \frac{\sum_{ij}\left[(\max(0,\ \Theta^{ij}(d) - \Theta_X^{-,i})^* w^{ij}(d)\right]}{\sum_{ij}\left[(\Theta^{fc,i} - \Theta_X^{-,i}(d))^* w^{ij}(d)\right]} \tag{9}$$

2.2. Model implementation

The model has been developed with the C++ language by using the Integrated Development Environment Eclipse and the CDT plug-in. It has been tested on Windows XP, VISTA and 7. BISWAT may be distributed as a dynamic link library (dll) or directly as a windows executable (if necessary, the model may be easily exported to Linux or others operating systems). The model implementation has been done by respecting C++ standards and by using possibilities offered by object-oriented programming. Moreover, the software architecture has been designed to facilitate modularity (e.g. having only one C++ class per biophysical process).

To run a simulation, the model requires 3 input files in the csv format: *input_variables.csv* which contains weather data and RIE dynamics; *parameters.csv* which contains all parameters and *crop_calendar.csv* which contains instructions for species sowing or destruction and daily irrigation. The model produces two output csv files: *output_variables.csv* which contains all main states variables computed by the model and *ouput_soil.csv* which contains all state variables of the soil cells.

To facilitate the analysis of simulations, the model is delivered with a R-script allowing to plot the major state variables dynamics (SWEP of each species and water flows). Also, a visualization tool has been designed in C++ by using the OpenCV library to display how the simulated soil part of the agrosystem evolves in real time (displaying of roots growth and water content in each soil sample at each time step).

2.3. Model evaluation

2.3.1. Experimental data

We evaluated, in comparison with soil water content measurements, the BISWAT model on 5 so-called reference agrosystems covering the target diversity of plant types and combinations: mono specific annual short cycle crop (e.g. salad), mono specific mature "tree" (e.g. vineyards, with root system established), bispecific mature tree (e.g. vineyard with perennial grass or annual legume alley-cropping), mono specific young tree (peach, with root system growing) and bispecific young tree (peach with perennial grass-legume mixture alley-cropping). Vineyards were 10 years old with a well-established canopy and roots while orchards had 2 year-old peach trees with root growth (in depth and width) during the simulated year. Table 2 lists the 22 data sets used in this study to evaluate the model: three datasets for mono specific salads coming from Gay (2002), where salads were cultivated under plastic shelters with sprinkler irrigation; six data sets for monospecific vineyards cultivated on a bare soil with or without drip irrigation (Guilpart et al., 2014; Pellegrino et al., 2004); four data sets for vineyards cultivated with an intercrop: an annual grain legume (chickpea, Pellegrino et al., 2004) or a perennial grass (tall fescue, Celette et al., 2008); six data sets for monospecific peach orchards with a drip irrigation and three data sets for bispecific peach trees orchards cultivated with a perennial grass-legume cover crop (Forey et al., 2016). All data sets come from experimental sites in southern France but with different soils and locations. Soil water content in these different data set was regularly measured with a neutron probe on different dates, depths (every 20 cm) and positions (on the crop row and in the middle of the inter-row) to allow for a robust assessment of the soil water dynamic simulation by the BISWAT model.

For salads, evaporation was contained by the presence of a plastic mulch on the soil and there was neither rain nor run-off due to the cultivation under plastic shelter. Crop cycles lasted from 50 to 90 days between plantation and harvest, with irrigation managed to avoid water stress throughout all the crop cycle (except for a few days before harvest). Once fully developed, salads covered the whole soil surface, thus intercepting most incident radiation. For these datasets, soil depth explored by roots was shallow (35–40 cm). For vineyards, most cases

were not irrigated (only one plot had drip irrigation); the crop cycle was much longer than salads, generally starting at the beginning of April and harvest occuring in September or October. For all vineyard scenarios, inter-row distances were the same (2.5 m) whereas soil depth varied from 2.5 m to 3.6 m and roots had already reached their maximum depth and width at the beginning of the simulation.

In peach orchards, trees were young (data obtained the year after trees planting) so roots were still in a net growth phase both in depth and width, which makes the estimation of the TTSW and FTSW more challenging. Peach tree cycle duration was similar to vineyard, but simulations stopped in august 2015 (i.e. before leaf senescence) due to lack of data on soil water content after this period. The inter-row distance was 3 m but as for the root system, the tree canopies were not fully developed - leaving a lot of light reaching the bare soil or the intercrop. Overall, we consider this dataset as providing a comprehensive test data for the evaluation of the BISWAT model as it challenges the model's ability to deal with the major process (including root growth) in a range of annual and perennial (in juvenile and mature phase) grown alone or in association and for different levels of soil water deficit due to climate, soil and irrigation management, in conditions representative of typical farmer's fields.

2.3.2. *Evaluation of the model*

The evaluation process was conducted in two steps: i) a first evaluation comparing measurements of soil water content for each date, soil layer and position to those simulated by the model and ii) a second evaluation process to estimate performance of BISWAT for water stress diagnosis, by comparing the SWEP estimated from measurements (following the protocol described by Pellegrino et al., 2004) with that simulated by the model. In the case of peach trees, due to the root growth, the water balance dynamics in the different soil compartments were too difficult to estimate from measurements (sampling was not sufficient) so we chose to evaluate the model on the SW state-variable instead of the SWEP (Sum of $SW^{ij}(d)$ for columns on the row and in the middle of the inter-row). Statistical indicators are those classically used to evaluate crop models (Wallach et al., 2014): the root mean square error (RMSE), the bias (σ), the model efficiency (EF) and the error max (Emax).

2.4. *Sensitivity analysis*

A combined uncertainty and sensitivity analysis was conducted in order to get some insights into the model inputs that either need to be measured with precision, or conversely that can be estimated roughly without causing noticeable uncertainty in the simulated SWEP. This analysis was repeated on the various agrosystems in order to give a broader picture of the model responses to model input uncertainty in typical situations of targeted model use. Input uncertainty is not the same depending on the system (for example, the variables describing the inter-crop can be uncertain for inter-cropped vineyards but may not be used on the salad system). Secondly, even if some input uncertainty may be modelled in the same way, its propagation may be different depending on climate and crop management (Roux et al., 2014a; Roux, 2017). For example, output uncertainty due to an uncertain $\Theta^{-}(z)$ is expected to be lower in well-watered conditions (such as salad), where soil water content is maintained above this limit, compared to rainfed intercropped vineyards, where this limit is frequently reached between two rainfall events.

This approach led to define a set of 19 scenarios: one for salad, four for monospecific vineyards with a small TTSW (TTSWs in Table 3) and four with a big TTSW (TTSWb), four for bispecific vineyards with a low TTSW and four with a high TTSW, one for the monospecific peach orchard, one for the bispecific peach orchard. More scenarios were considered in vineyards because it is generally a non-irrigated agrosystem for which the sensitivity of the results to soil and climate variability should be discussed and because very contrasted soil water

Table 3
List of factors for the sensitivity analysis and for each of them, the reference value and the explored interval (for vineyards TTSWs means "small TTSW" and TTSWb means "big TTSW").

	Factors	Unit	1. Salads under cover	2. Monospecific vineyard (TTSWs)	3. Monospecific vineyard (TTSWb)	4. Bispecific vineyard (TTSWs)	5. Bispecific vineyard (TTSWb)	6. Monospecific peach tree	7. Bispecific peach tree
RIE	RIEmax_A	W.m-2/W.m-2	0.95 ± 0.05	0.45 ± 0.05	0.45 ± 0.05	0.45 ± 0.05	0.45 ± 0.05	0.35 ± 0.05	0.35 ± 0.05
	RIEmax_B	W.m-2/W.m-2	–	–	–	0.75 ± 0.05	0.75 ± 0.05	–	0.95 ± 0.05
Roots	Erdmax_A	mm	450 ± 100	1000 ± 200	2500 ± 300	1000 ± 200	2500 ± 300	1000 ± 200	1000 ± 200
	Erdmax_B	mm	–	–	–	1000 ± 200	1000 ± 200	–	500 ± 100
	TsToReachErdMax_A	°C	420 ± 50	–	–	–	–	3000 ± 500	3000 ± 500
Plant/Soil	Θ-A(z)	m3.m-3	[0.14/0.17/0.25/0.30] ± 0.02	[0.07/0.07/0.12/0.15/0.16/0.16/0.16] ± 0.02	[0.07/0.07/0.12/0.15/0.16/0.16/0.16/0.19/0.21/0.21/0.18/0.21] ± 0.02	[0.07/0.07/0.12/0.15/0.16/0.16/0.16] ± 0.02	[0.07/0.07/0.12/0.15/0.16/0.16/0.16/0.19/0.21/0.21/0.18/0.21] ± 0.02	[0.12/0.12/0.18/0.19/0.19/0.19] ± 0.02	[0.12/0.12/0.18/0.19/0.19/0.19] ± 0.02
	Θ-B(z)	m3.m-3	–	–	–	[0.06/0.06/0.09/0.15/0.15/0.15/0.17] ± 0.02	[0.06/0.06/0.09/0.15/0.15/0.15/0.17/0.20] ± 0.02	–	[0.13/0.13/0.19/0.19] ± 0.02
Soil	Θfc(z)	m3.m-3	[0.27/0.27/0.32/0.34] ± 0.02	[0.24/0.24/0.24/0.27/0.28/0.30/0.28] ± 0.02	[0.24/0.24/0.24/0.27/0.28/0.30/0.28/0.28/0.29/0.29/0.27/0.28] ± 0.02	[0.24/0.24/0.24/0.27/0.28/0.30/0.28] ± 0.02	[0.24/0.24/0.24/0.27/0.28/0.30/0.28/0.28/0.29/0.29/0.27/0.28] ± 0.02	[0.23/0.23/0.24/0.25/0.26/0.25] ± 0.02	[0.23/0.23/0.24/0.25/0.26/0.25] ± 0.02
Evaporation	ThreshEvap1	mm	–	5.5 ± 2.5	5.5 ± 2.5	5.5 ± 2.5	5.5 ± 2.5	5 ± 3	5 ± 3
	ThreshEvap2	mm	–	20.5 ± 1.5	20.5 ± 1.5	20.5 ± 1.5	20.5 ± 1.5	17 ± 1	17 ± 1
Runoff	CN2Bare	–	–	94 ± 2.5	94 ± 2.5	94 ± 2.5	94 ± 2.5	89 ± 2.5	89 ± 2.5
	CN2Crop	–	–	–	–	84 ± 2.5	84 ± 2.5	–	84 ± 2.5
Explored years:			1	4	4	4	4	1	1

content in this system can be found. These 19 scenarios and the uncertainty of the relevant inputs are defined in Table 3 and represent what experts in input variables measurement have considered as relevant (following the approach of Roux et al., 2014b).

For each scenario, the input uncertainty was propagated using a Monte-Carlo procedure in order to compute the distribution of model output. As the SWEP model output is dynamic, we simplified the problem by analysing only the mean absolute error over time from the reference simulation associated with the scenario under study.

The uncertainty distribution was described by its mean, its standard deviation and its maximum. We also conducted variance based sensitivity analysis in order to rank the inputs of the scenarios exhibiting the highest uncertainty levels. Total Sensitivity Indices (Sobol, 1993), which quantify the overall effect of a single input on the model output, were computed using a Sobol algorithm (Jansen's algorithm; Jansen, 1999; Saltelli et al., 2010) as implemented in the R package "Sensitivity" (Pujol et al., 2017).

3. Results: model testing and assessment

3.1. A model able to simulate a large range of agrosystems

We tested how the BISWAT parametrization concepts and protocol apply to the 5 reference mono and bispecific types of agrosystems illustrated with salad, vineyards and peach orchards (see Section 2.3.1). We focus here on parametrization. Evaluation of model error with the 22 measured datasets will be discussed in the next section. A more extensive exercise of model parameterization for all types of agrosystems found in a typical Mediterranean region has been conducted successively with local advisors, in the surrounding of Montpellier: 10 types of vineyards, 6 types of orchards (apple, apricot, peach), melon, salad, tomato, durum wheat and maize (Bertrand and Wery, 2017). In our reference situations (e.g. with all parameters measured), the salad case illustrates the ability of the model inputs to represent an annual crop reaching full ground cover, characterized by a short growing cycle and rapid aerial and below-ground growth, and for which the farmers objective is to avoid any water stress, using drip irrigation. The intercropped vineyard is a typical perennial-based and vertically stratified system with respect to light competition: the vine intercepts a part of the incoming radiation that will not be available for the intercrop. This system is different from the previous example in terms of water-related crop processes because vines has the remarkable ability to regulate its transpiration even for very low levels of soil water deficits (i.e. < -100 mbars of soil water potential or < 0.15 MPa of pre-dawn leaf water potential; Pellegrino et al., 2006), which is typical of an iso-hydric plant behaviour. The vineyard agrosystem also includes competition for water by an intercrop sown between vines rows and destroyed following a dedicated management plan (most often at burdbust). The peach orchard case combines the different specificities of the previous agrosystems: stratification coming from light competition, intercropping with an intercrop inducing competition for water, rapid shoot and root growth (the latter along two directions, along the tree row and orthogonal to the row).

Fig. 3 shows how the main parameterization concepts have been used for these reference agrosystems. Following the approach of Roux et al. (2014b) for model assessment, in the reference situation all parameters values have been set by using experimental data presented in Section 2.3.1. The flexibility of the soil sampling and the parameterization of the root growth in BISWAT with the Erd and Erw concepts, allowed to account for the various rooting depths depending on soil structure and rooting pattern, while avoiding the data-intensive parameterization required in the "integrated models" for mono-specific (e.g. Hammad et al., 2017) or pluri-specific (e.g. Luedeling et al., 2016) agrosystems. We used four layers between 0 and 0.6 m for the salad system, 14 layers between 0 and 2.6 m for the vineyard system, 8 layers between 0 and 1.5 m for the peach orchard. The effective rooting depth (Erd) and width (Erw) was used to simulate, in a simple way, the dynamic of root positioning and growth for the salad and peach systems while it was considered as constant for the vineyards and dynamic for their intercrops. Measured *ErdMax* were 0.35 m (salads), 2.5 m (vineyard), 1 m (intercrop in the vineyard), 0.9 m (peach trees), 1 m (intercrop in the peach orchard). Measured *ErwMax* were 0.125 m (salads), 1.25 m (vineyard), 0.75 m (intercrop in the vineyard), 1.35 m (peach trees) and 1.5 m (intercrop in the peach orchard).

The use of measured RIE (driving evaporative demand partitioning in the system), as a forcing variable (i.e. given as an input to the model) allowed to integrate the influence of process not simulated by BISWAT but actually occurring in the fields, such as, shoot growth (e.g. depending on the level of nitrogen supply managed by the farmer to be non limiting for salad and suboptimal for vineyard grape quality and sensitivity to disease), tree density, inter-row spacing and tree pruning. The rapid growth of salad canopy was modelled using a fast growing RIE (see Fig. 3). When salads entirely cover the soil (due to high plant density and non limiting N supply), RIE was fixed to its maximum (equal to one in this case as no soil was anymore visible between plants). The sowing and harvest dates of the intercrop for the vineyard and peach systems were defined using the RIE dynamics of the intercrop by having a RIE to 0 before sowing and after its destruction. The maximum value of 0.45 and 0.22 for the RIE of the vine and peach trees respectively (which takes into account the large inter-row distance and the tree pruning to allow for tractor's traffic), were set when plants had reached their maximum vegetative leaf development. At this time, 45% (resp. 22% for peach trees) of the light coming on the whole field is intercepted by vines (resp. peach trees), which causes, in our model, a 45% (resp. 22%) reduction of the maximum soil potential evaporation or intercrop potential transpiration.

In the BISWAT model, TTSW is considered as a state variable as we simulate, when relevant, plant root growth in both directions (y and z) with Erd and Erw and the model may be parameterized with very contrasted rooting characteristics (e.g shallow (35 cm) and narrow (12.5 cm) for the salad vs. deep (2.5 m) and large (1.25 m) for the vineyard). Moreover, the use of 2 discretized water limits $\theta^{fc}(z)$ and $\theta^{-}(z)$ allowed us to model different soils using $\theta^{fc}(z)$ and different rooting densities or plant hydric behaviour using the $\theta^{-}(z)$. For example, in the case of intercropped vineyards, $\theta^{-}(z)$ of the intercrop in Figure (3) is lower or equal than $\theta^{-}(z)$ for the vine near the soil surface in order to account for a more important water uptake by the intercrop in soil surface layers due to higher root density and to the anisohydric behaviour of the intercrop (tall fescue or chickpea) compared to vineyard which has a isohydric behavior (and therefore a θ^{-} remaining well above θ^{fc}). From our experience on a large range of crops, it is likely that the anisohydric behavior (i.e. a lower sensitivity of stomata closure to soil drying) leads to a lower predawn leaf water potential (e.g. -2.5 MPa for coton in Lacape et al., 1998) allowing plants to extract water closer to the permanent wilting point than a isohydric behavior for which early stomata closure maintain predawn leaf water potential above -1.5 MPa (e.g. for vineyards in Pellegrino et al., 2004). On the other hand, water will be only uptaken by vineyards for larger depths through the settings $\theta^{-}_{vineyard} < \theta^{fc}$ until 2.5 m (= $ErdMax_A$) whereas there is no uptake by the intercrop below 1 m (=$ErdMax_B$).

3.2. A model containing the error of simulation for a large range of agrosystems

We present the evaluation results obtained with the BISWAT model on the five reference agrosystems and the 22 datasets with soil water content measurements (see Section 2.3.1): salads, mono and bispecific vineyards, mono and bispecific peach orchards. These evaluations cover a large range of contrasted situations in terms of humidity and water stress: SWEP measurements range from 0 to 0.9 for salads, from 0.04 to 0.97 for vineyards, and SW measurements vary from 79 mm to 330 mm for peach orchards. Fig. 4 shows the graphical comparison between

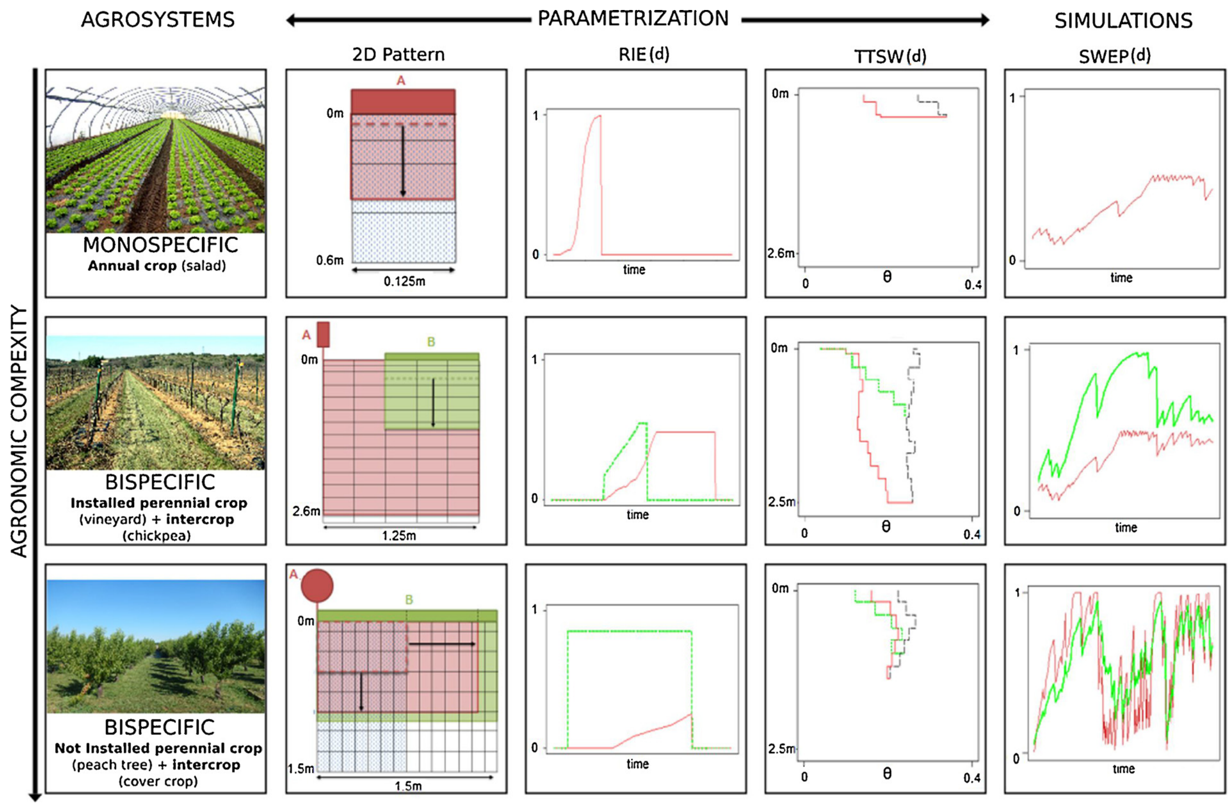

Fig. 3. Parameterization of the BISWAT model for a series of contrasted agrosystems. Red line represent plant A (vineyard or peach tree), green lines represent the intercrop (plant B) and black lines represent soil water holding capacity at field capacity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

predictions and measurements for the five types of agrosystems. Results are presented for variables θ and SWEP for salads (three data sets) and vineyards (10 data sets) and for both variables θ and SW for peach trees (nine data sets) for the reason explained in Section 2.3.2. Table 4 summarizes these results using statistical indicators presented in Section 2.3.2.

We have chosen to show separately the results for monospecific and bispecific agrosystems because there is *a priori* no reason to have the same level of model performance. The increasing complexity of agrosystems (starting from monospecific salads with a very short cycle without several processes like rain, runoff and evaporation to bispecific peach trees with a root system still in a growing phase and all the above-mentioned flows) seems to be not correlated with model error. We obtained the same level of performance between monospecific and bispecific systems, with slightly better results for bispecific systems (for vineyards SWEP, RMSE are 0.099 and 0.049 respectively) and for peach orchards SW, RMSE are 17.2 mm and 11.1 mm respectively).

These data show that there is no systematic trend to over- or underestimate the simulated state variables as overall we obtained low absolute values for the bias: bias on salads are opposite for θ (-0.009 m3.m-3) and SWEP *(0.038*m3.m-3*);* bias on vineyards are predominantly negative (for θ, respectively -0.001 m3.m-3 and -0.005 m3.m-3 for mono and bispecific and for SWEP, respectively -0.056 and -0.003 for mono and bispecific vineyards and 0.021 for the intercrop); bias on peach orchards were all positive (for θ, respectively 0.009 m3.m-3 and 0.008m3.m-3 for mono and bispecific and for SW, respectively 9.2 mm and 4.3 mm for mono and bispecific peach orchards). The effectiveness of BISWAT was assessed with the RMSE indicator, which has the advantage of being expressed in the same unit as the state variable. For θ, the RMSE ranges from 0.025 m3.m-3 to 0.028m3.m-3 for the five reference agrosystems. For SWEP, the best score was obtained for the bispecific vineyard (0.049) and the worst was for salads (0.123). For SW, we obtained respectively 11.1 mm and 15.3 mm for monospecific and bispecific peach orchards which is accurate when related to the average of 244 mm observed for SW. Simulations have shown that maximum errors are quite low, ranging from 0.089 m3.m-3 to 0.195 m3.m-3 for θ, from 0.118 to 0.294 for SWEP and from 23.4 mm to 50.2 mm for SW. Overall we obtained high values for model efficiency (between 0.799 and 0.964 for SWEP and SW respectively). We also observed a trend of better results (i.e. higher efficiency) for the SWEP and SW state variables than for θ.

We consider that these results demonstrate a high level of performance obtained with the BISWAT model in simulating water stress dynamics for a large range of reference agrosystems.

3.3. A particular attention to give to few parameters in order to contain the uncertainty

We present the results of the combined uncertainty and sensitivity analysis conducted with the BISWAT model on a total of 19 scenarios. For each factor in each scenario, reference value and interval are those defined in Table 3. Results of these analyses are summarized in Table 5.

The mean uncertainty obtained across all scenarios on the SWEP state variable (Table 5) varies from 0.0134 (scenario 13) to 0.0489 (scenario 19), the standard deviation varies from 0.0072 (scenario 13) to 0.0252 (scenario 7) and the maximum error varies from 0.0479 (scenario 5) to 0.1524 (scenario 6). These results are satisfactory as the uncertainty is quite limited whereas the explored intervals are rather large (e.g. ± 0.02m3.m-3 for Θ_A^- and Θ^{fc}, ± 0.05 for $RIEmax_A$ and until ± 30 cm for $Erdmax_A$) and may correspond to errors which may be reasonably done by a model user who frequently work outside of the reference situation for parameters measurements as shown by Roux et al. (2014b).

We focus below on scenarios where uncertainty has been considered

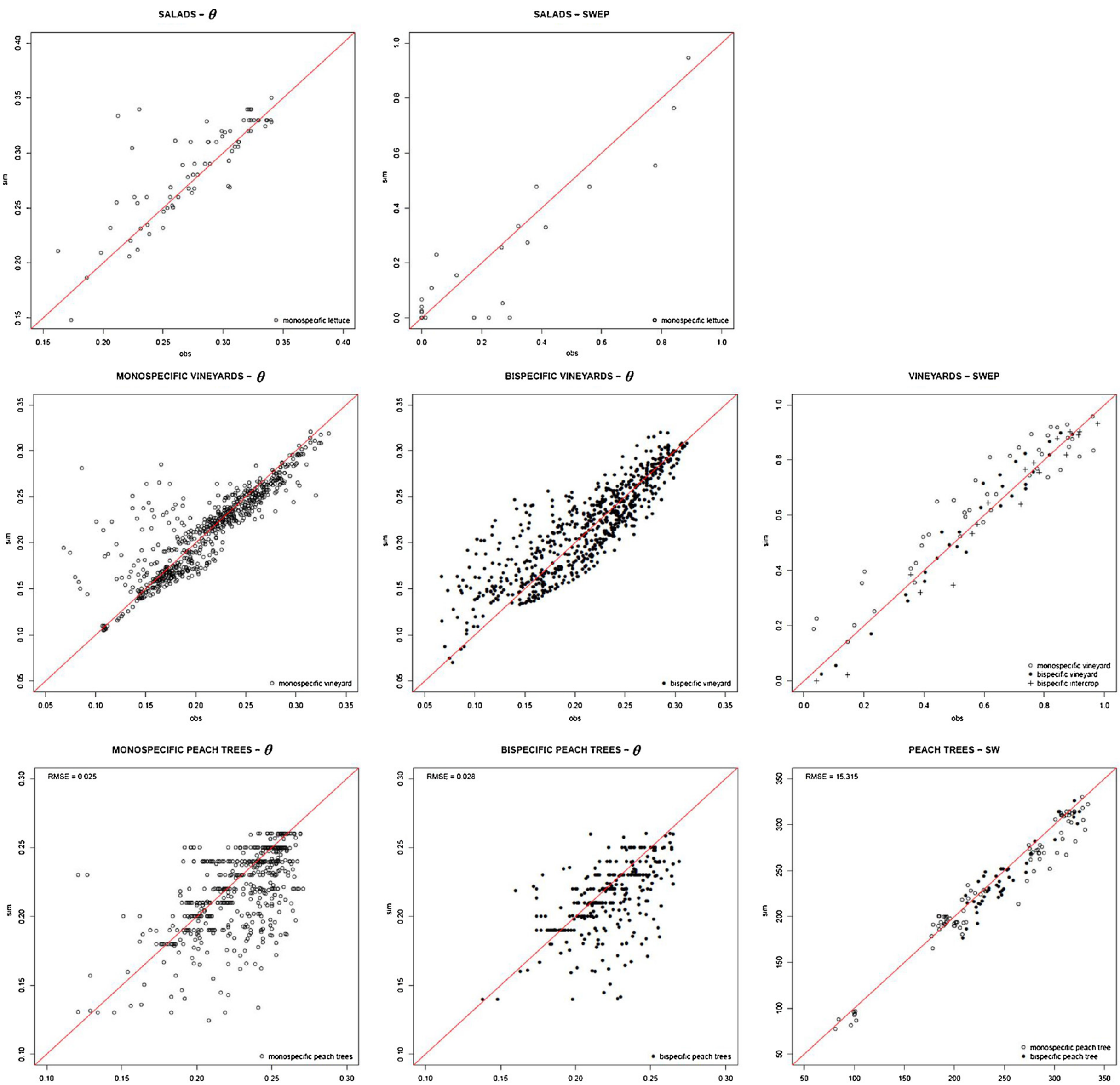

Fig. 4. (a–c): Evaluation results obtained for the 5 reference agrosystems for the three state variable: θ(z,d), SW(d) and SWEP (d): graphical representation illustrating the comparison between simulation and measurements.

Table 4
Evaluation results obtained for the 5 reference agrosystems for the three state variable: θ(z,d), SW(d) and SWEP(d): computation of 4 statistical indicators: RMSE, Bias, Efficiency and maximum error.

	SALADS		VINEYARDS					PEACH ORCHARDS			
	mono		mono		bi			mono		bi	
	θ	SWEP	θ	SWEP	θ	SWEP_A	SWEP_B	θ	SW	θ	SW
RMSE	0.028	0.123	0.026	0.099	0.028	0.049	0.061	0.025	17.246	0.028	11.100
Bias	−0.009	0.038	−0.001	−0.056	−0.005	−0.003	0.021	0.009	9.192	0.008	4.346
Efficiency	0.597	0.799	0.746	0.852	0.749	0.949	0.943	0.044	0.885	−0.024	0.964
ErrorMax	0.122	0.294	0.195	0.205	0.107	0.118	0.149	0.089	50.204	0.109	23.396

as important (maximum error higher than 0.1). These scenarios are highlighted in grey in Table 5 and represent only 10 out of the 19 scenarios. In Table 5, average sensitivity and maximum sensitivity have been computed for the 10 most uncertain scenarios and factors were ordered according to their average sensitivity.

For factors having an average sensitivity index below 0.05 ($Erdmax_B$, $TsErdmax_A$, $ThreshEvap1$, $ThreshEvap2$, $RIEmax_B$ and $CN2_{crop}$), we considered that they have a low impact on the SWEP state variable so we did not included them into Table 5. Θ_A^- is the most sensitive factor as it has the greater sensitivity average (0.648) and it ranks predominantly first (six times out of 10) or second (three times out of 10) in the sensitivity ranking. The two other main sensitive

Table 5

Uncertainty and Sensitivity analysis conducted with the BISWAT model by using the SOBOL algorithm. Scenarios highlighted in grey are those where uncertainty has been considered as significant (with a maximum error higher than 0.1). Sensitivity indices (Total Sobol Indices) which are in bold correspond to the 3 most sensitive factors of each scenario and their exponents indicate their ranking (the 1st one is colored in red) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

Simulations				Uncertainty			Sensitivity index					
ID	Description	Intial state	Rainfall	Max	Mean	Sd	Θ^{-}_{A}	Θ^{fc}	$Erdmax_A$	Θ^{-}_{B}	$RIEmax_A$	$CN2_{Bare}$
1	Monospecific salads	wet	-	0.1315	0.0366	0.0239	**0.682^{2}**	**0.720^{1}**	**0.249^{3}**	NA	0.134	NA
2	Monospecific vineyards (low TTSW)	wet	wet	0.112	0.0337	0.0181	**0.531^{2}**	**0.213^{3}**	**0.590^{1}**	NA	0.187	0.205
3		wet	dry	0.1018	0.0277	0.0173	**0.560^{2}**	**0.403^{3}**	**0.744^{1}**	NA	0.226	0.002
4		dry	wet	0.1179	0.0428	0.022	0.048	**0.165^{2}**	0.058	NA	**0.093^{3}**	**0.961^{1}**
5		dry	dry	0.0479	0.0161	0.0075	0.398	0.246	0.435	NA	0.212	0.299
6	Monospecific vineyards (high TTSW)	wet	wet	0.1524	0.0367	0.0245	**0.755^{1}**	**0.583^{2}**	0.232	NA	**0.313^{3}**	0.162
7		wet	dry	0.1396	0.0366	0.0252	**0.754^{1}**	**0.699^{2}**	0.245	NA	**0.286^{3}**	0.001
8		dry	wet	0.0937	0.0308	0.0161	0.182	0.095	0.037	NA	0.214	0.871
9		dry	dry	0.0568	0.016	0.009	0.726	0.481	0.209	NA	0.342	0.095
10	Bispecific vineyards - (low TTSW)	wet	wet	0.0899	0.0261	0.0139	0.710	0.438	0.560	0.035	0.039	0.046
11		wet	dry	0.0818	0.0216	0.0133	0.659	0.399	0.601	0.046	0.047	0.001
12		dry	wet	0.0866	0.0273	0.0124	0.313	0.265	0.395	0.198	0.033	0.465
13		dry	dry	0.0491	0.0134	0.0072	0.636	0.125	0.359	0.223	0.057	0.042
14	Bispecific vineyards - (high TTSW)	wet	wet	0.1201	0.0326	0.0215	**0.812^{1}**	**0.603^{2}**	**0.245^{3}**	0.032	0.108	0.025
15		wet	dry	0.1313	0.0331	0.0227	**0.728^{1}**	**0.609^{2}**	**0.275^{3}**	0.028	0.123	0.000
16		dry	wet	0.064	0.0203	0.0103	0.587	0.270	0.104	0.233	0.116	0.359
17		dry	dry	0.0594	0.0152	0.0097	0.758	0.418	0.223	0.106	0.154	0.015
18	Monospecific peach orchards	wet	dry	0.1286	0.0317	0.0212	**0.782^{1}**	**0.659^{2}**	0.136	NA	**0.187^{3}**	0.002
19	Bispecific peach orchards	wet	dry	0.1448	0.0489	0.0236	**0.831^{1}**	**0.318^{3}**	0.043	**0.460^{2}**	**0.010**	0.000
						Average sensitivity:	**0.648**	**0.497**	**0.282**	**0.173**	**0.167**	**0.151**
						Maximum sensitivity:	**0.831**	**0.720**	**0.744**	**0.460**	**0.313**	**0.961**

parameters were those involved in the parameterization of TTSW of the main crop: firstly Θ^{fc} with an average of 0.497 and a maximum of 0.720 and secondly $Erdmax_A$ with an average of 0.282 and a maximum of 0.744. The remaining factors like $RIEmax_A$, Θ^{-}_{B} and $CN2_{bare}$ were also sensitive but less than those related to TTSW. Particular attention must be given to the $CN2_{bare}$ factor which has a quite low sensitivity average (0.151) compared to other factors but a very high maximum error (0.961), obtained in a specific scenario (a vineyard with a low TTSW, a dry soil at budburst and a very wet climate during the cycle) which is a typical situation of high risk of runoff.

Moreover, we also observe that the ranking of factors strongly depends on scenarios. For example, scenarios 2, 4 and 6, which correspond to monospecific vineyards with a low or high TTSW and a wet or dry climate give different ranking for the three first factors: in the order from the most sensitive to the less sensitive $Erdmax_A$, Θ^{-}_{A} and Θ^{fc} for scenario 2, $CN2_{Bare}$, Θ^{fc} and $RIEmax_A$ for scenario 4 and Θ^{-}_{A}, Θ^{fc} and $RIEmax_A$ for scenario 6.

4. Discussion: model validity domain and parameterization protocol

The combined use of flexible soil descriptions and integrative concepts such as RIE and TTSW (via θ^{fc} (z) and θ^{-} (z)) appeared sufficient to represent the main specificities of the contrasted test cases of agrosystems based on salad, vineyards and peach orchards and to allow for the computation of the SWEP dynamics for each plant when grown alone or in association. The protocol of parameterization (e.g. Fig. 2 for RIE) was robust enough to further apply the model for the various types of agrosystems of a typical Mediterranean region (Bertrand and Wery, 2017) making use of existing data and local expertise on soils, plants and management in farmers fields.

The model run with these parameters on the contrasted reference agrosystems also led to acceptable levels of error. Crop model evaluation is a complex issue, essentially due to the lack of data often required to set all model parameters but also to compare model outputs with measurements on the output variable for which the model is going to be used (i.e. the SWEP water stress index dynamic of each plant in our case and not only the soil water content as done in most model assessment). This issue is even more emphasized in the case of pluri-specific agrosystems due to the multiplicity of plant parameters and of possible spatial and temporal plant combinations. In this study, datasets used for the model evaluation involved five contrasted mono-specific and bi-specific agrosystems. The evaluation results show that the BISWAT model was able to simulate the water stress dynamics of these agrosystems satisfactorily, when compared with experimental measurements, for both monospecific and bispecific agrosystems. Good results were obtained on the SWEP state variable for both the main crop and the intercrop, which is important as both are needed to understand the field situation. Moreover, in the case of vineyards, accumulated water flux data (which are not presented in this paper) like soil evaporation, plants transpiration and runoff were quite similar to values obtained with the WaLIS model (Celette et al., 2010). On the basis of these evaluation results, we conclude that the BISWAT hypotheses, concepts and mathematical formalisms provide a good trade-off between model complexity and model performances on this wide range of agrosystems. Moreover, even if specific evaluations are required before using the model for new crops or new agricultural conditions, the choice of very contrasted reference agrosystems used in this study allow us to be optimistic concerning the extrapolation of the model performances.

The uncertainty and sensitivity analyses conducted on the five reference agrosystems give to the BISWAT's users some tangible elements to tackle the question of model parameterization depending on data availability (Roux et al., 2014b). Generally speaking, uncertainty in a model output results from the precise degree of uncertainty in the input, which depends on how an input value was obtained

(measurement, expert knowledge, bibliography) and how this uncertainty propagates into the model output in interaction with all other uncertainties. The degree of input uncertainty in our analysis was represented by the choice of uncertain inputs in typical situation of model use and by the width of intervals in Table 3. Model inputs, easy to obtain with usual and robust measurements, were not included (weather, crop management, geometry) and other inputs often difficult to access have been considered with moderately pessimistic uncertainty, taking into account the specificities of our reference systems. For example different uncertainties in rooting depth were used for salad and the deep-rooted vineyard. As a result, given our uncertainty and sensitivity results (Table 5), some approximated procedures may be used to estimate inputs having a low sensitivity index - keeping in mind that these procedures should not be too approximated when compared to the uncertain intervals of Table 3 otherwise our sensitivity results become inapplicable. This is the case for the dynamic RIE input: it has a low sensitivity index and may therefore be obtained in an easy but approximated way using several dates (depending on the plant phenology, e.g leaf emission starting and ending and senescence starting and ending) and by estimating *RIEmax* from field observations (tree density, height and width of the crown, leaf area, crop cover rate, etc.) and by making linear interpolations between each date (see Fig. 2). This is also mostly the case for evaporation and runoff parameters for which bibliographical estimates appear sufficient, except for vineyards with a low TTSW, a dry soil at budburst and a very wet climate during the vegetative growth period. However, for parameters related to the TTSW, expert knowledge should be used with a great care as we showed that these parameters are very sensitive: too approximated values would surely propagate errors into the model output. In this case, the TTSW of each plant in the given soil should better be measured with the protocol described in Pellegrino et al. (2004). The approximations procedures should also be precisely characterized in terms of uncertainty as done in Roux et al. (2014b).

The drawback of such partial and low-data approach of modelling is a poor and potentially uncertain representation of some processes which may have been of minor importance in the situations were we tested the model, in front of measured data and in the sensitivity analysis, but which could have a significant impact in specific situations. For example the maximal soil evaporation or cover crop transpiration under the shade of a tree may be under-estimated by our model in which it is driven by the interception of incident radiation, while in reality it is driven by net radiation. In this case it is the user's responsibility to understand the validity domain of the model and skip for this particular study to other models already addressing these conditions. For other simplifications such as the limitation of evaporation to the first 10 cm soil layers in our model, which is likely to underestimate this process in dry conditions, the model could be easily adapted to take this into account.

5. Conclusion: model originality and potential uses

The BISWAT model developed in this study is an original contribution to the simulation of water stress and water flows in bi-specific agrosystems organized in rows and combining trees (including grapevine) and crops. More than a breakthrough in modeling concepts, the novelty is rather in the way existing and robust concepts (e.g. partitioning of climatic demand with RIE or Plant Transpirable Soil Water) have been combined and operationalized in parameterization protocol allowing to use the model outside of research stations and for a wide range of bi-specific crops across a region and as they are managed by farmers. From our experience of collaboration with models users (reported for example in Roux et al., 2014b) this is a challenge for modelers because it either limit the use of their model in agriculture or it induces large and unknown uncertainties as they are most often used outside of what we call the « reference situation » where all model parameter are properly measured as in experimental station.

BISWAT has been designed as a "field-level partial model of water-limited bi-specific systems" in order to address questions when water is a major limiting factor. So it should be seen as a preliminary approach to more complex models integrating nutrients and yield determination of mono-specific agrosystems (e. CERES, Hammad et al., 2017) or agroforestry systems (Luedeling et al., 2016) as well as a more in-depth representation of energy and water balance. It can be seen as a low-data demanding step in the analysis of the impact of such plant association and management options at field level on water flows, before using it as a spatially distributed water balance model at watershed level (e.g. Arnold et al., 2012) or upgrading it into a water-limited yield simulation model (e.g. Paredes et al., 2014).

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